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Abstract

The Great Recession (the fourth quarter of 2007 through the second quarter of 2009) has been characterized by high rates of foreclosures and unemployment. Using a sample of community reinvestment loans, we examine the impact of structural unemployment and cyclical unemployment on mortgage terminations (default and prepayment). We find that mortgage default and prepayment are more sensitive to changes in the structural component of the local unemployment rate than in the cyclical component. In addition, depending on whether

structural unemployment rates are high or low, borrowers and lenders react differently to the incentives to terminate a loan.

Introduction

The Great Recession and its slow recovery changed in the first quarter of 2009 from one driven by the boom and bust of the subprime mortgage market to one driven by worsening employment conditions. Since employment (with its associated income stream) is a precondition for most households to meet their financial obligations, a weak labor market should increase mortgage delinquency and terminations. The unemployment rate has often been used as a proxy for adverse trigger events or negative income shocks. Not surprisingly, the unemployment rate has indeed been found to be positively associated with mortgage delinquency (Campbell and Dietrich 1983). Job loss can also force a household to move to a cheaper house or to become a renter. However, there is little empirical evidence to support this impact (Clapp et al. 2001). In general, empirical evidence indicates that job loss, as proxied by the unemployment rate, makes it more difficult to refinance existing mortgage debt, thus suppressing mortgage prepayments and refinances (Campbell and Dietrich 1983; Deng et al. 2000; Clapp et al. 2001, and An et al. 2010).

The relationship between the unemployment rate and default is less clear cut. For example, some papers find that higher rates of unemployment are associated with elevated rates of default and foreclosure (Capozza et al. 1997; Elmer and Seelig 1999, and Pennington-Cross and Ho 2010). Deng et al. (2000) find that the state unemployment rate is positively associated with mortgage default risk for the United States, however, for some key states such as California and Texas no statistically significant result is found. Other empirical studies do not find a relationship between default and unemployment rates (Clapp et al. 2001; Pennington-Cross and Chomsisengphet 2007, and An et al. 2010, and Ghent and Kudlyak 2011).

Why does the unemployment rate have the expected impact in some empirical studies but not in others? In this study, we examine the relationship between the local unemployment rate and mortgage terminations from a novel perspective. We contend that differences in unemployment rate across different locations and time periods may reflect different types of unemployment and that these different types may have differential impacts on the ability of borrowers to make timely mortgage payments or cure delinquent mortgages.

Within business cycle theory, the unemployment rate can be viewed as a combination of a structural component and a cyclical component. Unemployment caused by long term mismatches between labor supply and demand is often referred to as structural unemployment while cyclical unemployment is associated with temporary labor market conditions. Those two components may have distinct patterns of movement and statistical properties (Mocan 1999), and thus, their impacts on mortgage performance may differ as well. Depending on how long a homeowner expects to be unemployed, the incentives to avoid mortgage delinquency and default should also differ. For example, expectations of a short duration of unemployment might inspire the homeowner to avoid foreclosure by accessing other financial assets (such as savings or assistance from other family members). In contrast, if the spell of unemployment is expected to be very long, then these assets may be better used to cover the costs of moving to a location with superior labor market conditions or covering other consumer or financial needs (for example, food and transportation costs). In addition, the response of the lender/servicer likely will vary depending on perceptions of the length of the unemployment spell. From a policy and macro perspective, understanding the role of structural and cyclical unemployment on mortgage terminations should provide valuable insights to develop more effective intervention programs.

If structural and cyclical local unemployment rates have distinct impacts on borrower behavior, the impact of the observed unemployment rate on mortgage default and prepayment reflects the combination of these two components. As a result, we explore the relationship between mortgage performance (mortgage default and prepayment) and different measures of unemployment using a sample of loans originated under auspices of Community Reinvestment Act between 1991 and 2007. More narrowly, we use the Beveridge-Nelson (BN) decomposition (Beveridge and Nelson 1981) and the Hodrick-Prescott (HP) filter (Hodrick and Prescott 1997) approaches to decompose the cyclical and structural components of local unemployment rates. We find that structural unemployment is a more important determinant of mortgage terminations than cyclical unemployment. Mortgages are most sensitive to changes in structural unemployment defined by the HP filter. Predictions about future foreclosures that rely, even in part, on observed unemployment rates are likely to differ depending on the magnitude of the cyclical and structural components in each locality.

The remainder of the paper is divided into four sections. The next section discusses the business cycle and the unemployment decomposition alternatives, followed by a description of the empirical strategy and the data. Finally, the empirical findings and their implications are presented.

Unemployment and the Business Cycle

A seasonally adjusted time series y can be viewed as the combination of a structural component and a cyclical component as follows

$$y_t = c_t + \tau_t \quad (1)$$

Where *c* is the cyclical component (this can be also referred to as the transitory, temporary, or short term component) and τ is the structural component (this can be also referred to as the trend, permanent, or long term component). Numerous approaches have been proposed to separate the cyclical component and the structural component in Eq. (1) (for a review, see Ozyildirim and Zarnowitz 2006) including the unobserved component approach (Harvey 1985), the BN decomposition, the HP filter, and the Band-pass filter (Baxter and King 1999).

These approaches are based on a number of assumptions about features of the structural and cyclical components that can lead to different decomposition results. For example, as applied to unemployment, the estimated structural component using the BN decomposition is often much closer to observed unemployment than that estimated using the HP filter. This is because the BN decomposition assumes correlated structural and cyclical components while the HP filter imposes a smooth shape on the structural unemployment rate. Another example is in the difference between the BN decomposition and the unobserved component approach. The unobserved component approach proposed by Harvey imposes a zero correlation between the structural component and cyclical component. Morley et al. (2003) and Sinclair (2009) introduce correlation in the structural models.

The least empirically complicated decomposition technique is the linear deterministic trend approach. However, this approach is not theoretically or empirically sound when the series is not stationary (Stock and Watson 1988). The existence of a unit root process indicates that a series is not stationary. Many tests have been designed to detect unit roots in time series including Dickey and Fuller (1981), Perron and Phillips (1988), and Perron (1989). We perform the Augmented Dickey-Fuller tests on the unemployment rates between 1990 and 2009 for 540 different counties in the US. The results show the US unemployment rate is an I(1) process (unit root in the level but not in the first difference).[Footnote1] Among the 540 counties examined, test statistics reject a unit root process at the 10 % level for only 12 counties. The same tests reject a unit root process of the first difference of unemployment rates for 534 counties. These results, combined with the fact that the test statistic is sensitive to de-trending techniques, indicates that it is necessary to examine decomposition techniques that do not require a series to be stationary. Hence, this paper uses the BN decomposition and the HP filter as two alternative de-trending techniques. The BN decomposition requires a series to be stationary in the difference and the HP filter does not require the series to be stationary. This dual approach allows us to see how sensitive the mortgage results are these imbedded assumptions in HP and BN.

BN Decomposition

The first difference of the non-stationary series *y* in Eq. (1) is *w*. *w* is stationary and it can be expressed as follows

$$w_t = \mu + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \cdots \quad (2)$$

Where μ is the expectation of *w* and ε_t is the uncorrelated disturbance term. Beveridge and Nelson (1981) show that the structural component can be expressed as:

$$\tau_t = y + (\textstyle\sum_1^\infty \phi_i)\varepsilon_t + (\sum_2^\infty \phi_i)\varepsilon_{t-1} + \cdots \quad (3)$$

and the cyclical component , c_t, is $(\sum_1^\infty \phi_i)\varepsilon_t + (\sum_2^\infty \phi_i)\varepsilon_{t-1} + \cdots$

HP Filter

The HP filter assumes the structural component,τ_t, in Eq. (1) is smooth over time and is estimated by solving the following equation.Footnote2

$$\min_{\{\tau_t\}}\{\textstyle\sum_t c_t^2 + \kappa \sum_t [(\tau_t - \tau_{t-1}) - (\tau_{t-1} - \tau_{t-2})]^2\} \quad (4)$$

Where κ determines how smooth the time series of τ_t is and larger values of κ correspond to more smooth time series. Compared to BN decomposition and some other decomposition procedures, the HP filter is relatively straightforward to implement. It is widely used for decomposing structural and cyclical components (Mocan 1999).

Empirical Strategy and Data

To examine the relationship between local unemployment rates and loan performance, we estimate a competing risk approach and follow the empirical strategy used by Deng et al. (2000), McCall (1996), and Pennington-Cross and Ho (2010).

Survival and Hazard Specification

Under the competing risk framework, loan default and prepayment are jointly modeled while addressing the data censoring issue. The estimation relies on the construction of the hazard and the survival functions, which are introduced as follows.

Let λ^r_i be the hazard rate of default ($r = D$) or prepayment ($r = P$) for loan *i*. The hazard is specified as:

$$\lambda_i^r(t|X_i(t), \theta_D, \theta_P) = \exp\left(\lambda_0^r(t) + X_i(t)^* \beta_r + \theta_r\right) \quad (5)$$

where λ^r_0 is the baseline hazard, $X_i(t)$ is a matrix of risk determinants that may or may not vary over time *t*, β_r are the risk determinate parameters to be estimated, and ϑ_r are the heterogeneity parameters to be estimated which are assumed to be independent of observed characteristics. The prepayment and default events are assumed to be independent and the corresponding survival function S_i is defined as:

$$S_i(t|X_i(t), \theta_D, \theta_P) = \exp\left(-\int_0^t [\lambda_i^D(s|X_i(t), \theta_D, \theta_P) + \lambda_i^P(s|X_i(t), \theta_D, \theta_P)]ds\right) \quad (6)$$

The log likelihood, LL, is expressed in discrete time assuming risk determinants are constant within each time interval.

$$LL = \sum_{uncensored} \log \lambda_i^r(t|X_i(t), \theta_D, \theta_P) + \sum_{all} \log S_i(t|X_i(t), \theta_D, \theta_P) \quad (7)$$

The baseline hazard is estimated using local regression, as motivated by Cleveland (1979) and others, to smooth the Kaplan-Meier hazards of prepayment and default. Let n_t be the population at time t and n_{rt} be the number of termination events of type r at time t. The Kaplan-Meier hazard for time t and termination type r is n_{rt}/n_t.

The smoothing parameters are set to maximize the Akaike Information Criteria (AIC), 0.32 for default and 0.27 for prepayment. Default is defined as the first month with an observed 90-day delinquency on a mortgage and prepayment as the month in which the loan is paid off prematurely. The specification of heterogeneity mass point p_m for group m, is defined in a logistic transformation to bound the probabilities between zero and one.

$$p_m = \frac{e^{q_m}}{\sum_m e^{q_m}} \quad (8)$$

where $q_m \in (-\infty, +\infty)$ and q_1 is normalized to 0 .

Local Unemployment Rate and Decomposition

Local area unemployment data from the Bureau of Labor Statistics provide unemployment information for each county and each series is seasonally adjusted using the Census X11 method.

The implementation of BN decomposition follows Newbold (1990). Assume that w_t in Eq. (2) follows an ARMA(p, q) process and let ϕ_1 through ϕ_p be the AR parameters. Let $\hat{w}_t(j)$ be the forecast of w_j at time t, and $\overline{w}$ is the mean of the forecast. The cyclical component is defined as follows:

$$ct = \sum_{j=1}^{q} (\hat{w}_t(j) - \overline{w}) + (1 - \textstyle\sum_1^p \phi_i)^{-1} \displaystyle\sum_{j=1}^{p} \sum_{1=j}^{p} [\phi_i(\hat{w}_t(q-j+1) - \overline{w})] \quad (9)$$

We need to determine a forecasting process for each of the 540 counties covered in the data. Since we are trying to find patterns for over 500 series, we rely on the Bayesian Information Criteria (BIC) or Schwarz criteria to determine the Auto-Regressive and Moving Average (ARMA) process. Each series allows for up to ARMA(4,4) with the default being AR(1).[Footnote3] The Schwarz criteria tend to select lower order ARMA processes. One hundred twenty-nine counties are determined to be ARMA(1,0) during the sample period.

The BN decomposition may be sensitive to the potentially less precise forecasting mentioned above as well as the extreme value in $\left(1 - \sum_1^p \phi_i\right)^{-1}$ in Eq. (9). This leads to unreasonable estimates of cyclical and structural components around 2009 when unemployment rate reached its historic high during the sample period. As a result, we revise the forecasting process of those counties to ARMA(1,0).

Since the analysis is done at the monthly frequency, the smoothing parameter for the HP filter is set to be 129,600 following Ravn and Uhlig (2002).[Footnote4] Given that the HP components estimated in the past are affected each time the data is extended, we create a separate measure based on the HP structural component ranking for a robustness check. Each month we rank counties according to the HP structural component from low rate to high. The higher the ranking (or "score"), the higher the relative HP structural component is. We then sum the ranking of all months within our sample period. Therefore, the final "score," or HP Ranking Score (HPRS), can be interpreted as a measure of how consistently the HP structural component is higher than that in other counties.

The relationship between the business cycle, local unemployment, and loan performance is examined in a later section in a series of experiments. Using the default and prepayment hazards coefficient estimates, probabilities are simulated to investigate the response to changes in the observed and structural components of the local unemployment rate.

Community Reinvestment Loans

The data for the analysis come from a national sample of community reinvestment loans.[Footnote5] The database contains information on approximately 46,000 loans originated to low- or moderate-income families that reside in low-income areas, minority areas regardless of family income, or any minority borrower regardless of income or location.

The analysis sample includes 30-year fixed rate home purchase loans originated in 1991 or later, excluding manufactured homes. Over 22,000 loans in 540 counties throughout the country have complete loan and borrower information. The hazard analysis is performed on a monthly basis for loan history (loan age) up to 120 months.

Table 1 includes a list of the explanatory variables and their definitions.[Footnote6] The variables are grouped into those only observed at origination and those observed repeatedly over the life of the loan. The borrower annual income normalized by the area median income (*inc_ami*) is used to test whether the relative income of the household makes it more susceptible to default or prepayment. However, low income in itself should not affect the probability of a loan prepay or default because it does not directly affect the value of the option to terminate the loan or the extent to which it is “in the money” to do so. The financial incentives should be driven by interest rates and home values. However, low income likely functions as a proxy for unobserved education, mobility, wealth, and transaction costs. Therefore, we anticipate that higher income will be associated with a lower probability of default and a higher probability of prepayment. Monthly mortgage debt payments normalized by borrower monthly income (debt to income ratio or *dti*) is also included. We expect that households with larger debt burdens will be more likely to default and prepay because they will be more susceptible to unobserved trigger events that could cause a loan to terminate such as divorce, health events, or job loss. Through a similar logic, a higher borrower credit score at origination (*fico*) is expected to decrease the probability of default and increase the probability of prepayment. Moreover, borrowers who have not paid their prior debt obligations are also less likely to pay their current and future debt obligations. At the same time, poor credit history will also make it more difficult for a borrower to find alternative mortgage financing in the event of a move or a decline in interest rates.

Table 1 Variable definitions and summary statistics

	Variable	Subcategory	Mean	Std dev	Note
Constant within each loan	*inc_ami*		0.589	0.158	Annual income divided by area medium income at loan origination.
	dti		0.275	0.074	The fraction of combined income that goes toward mortgage payments or *front-end ratio*.
	fico		678	64	Borrower's credit score at loan origination
	Loans		22,538		
Varies within each loan	*default*		0.010	0.003	The first 90-day delinquency on a mortgage.
	prepay		0.003	0.001	A mortgage is paid off prematurely.
	cltv		0.788	0.150	Current loan amount divided by estimated house value.
	cltv12		0.760	0.140	One year forecast of *cltv*.
	refi		0.055	0.078	Percentage reduction in present value of future payments if refinance into the market rate as a fraction.
	refi12		0.062	0.073	One year forecast of *refi.*
	unempr	Observed	5.430	1.814	County level unemployment rate (percent).
		Cyclical HP	0.001	0.994	Cyclical component of "Level" measured by HP filter.
		Cyclical BN	0.006	0.193	Cyclical component of "Level" measured by BN decomposition.
		Structural HP	5.429	1.530	Structural component of "Level" measured by HP filter.
		Structural BN	5.436	1.841	Structural component of "Level" measured by BN decomposition.
		HPRS	62147	29999	Sum of county unemployment ranking by structural HP.
	ndecl		0.850	2.638	Number of months house price has continuous decline
	varmrate	1.5E-05	1.1E-05	24-month forward-looking variance of national mortgage rate.	
	varhpi		2.2E-05	4.1E-05	24-month forward-looking variance of quarterly percent change in MSA level house price index by Federal Housing Finance Agency.

	dsrts		113	61	Total Days since Foreclosure Referral to Sale, Cutts and Merrill (2008)
	loan age		45	28	Months
	Observations		968,561		

default and *prepayment* are the monthly hazard rates. HPRS sums the unemployment rate (Structural HP) county ranking for each month. The higher the individual ranking, the higher the Structural HP unemployment rate is that month. Different interest rates are tested for estimating *refi* and the results are robust to specifications. Missing values in variables lead to different sample sizes for different specifications. Sample size of the baseline specification is reported here and estimates for common variables are robust as shown later

A high loan-to-value ratio is associated with higher probabilities of default (Kau et al. 1994). *cltv* is estimated using the outstanding balance on the loan and an estimate of current house value generated through Federal Housing Finance Agency's metropolitan area house price index. A borrower's decision to terminate a loan is also influenced by expectations of future house prices, interest rates, and the length or cost of defaulting. We include three variables that will be discussed later in greater detail: a forecast of the future loan-to-value ratio (*cltv12*), a forecast of the future net present value percentage gain on a refinance (*refi12*), and a measure of number of days from the start of foreclosure proceedings to the day the property is referred for sale (*fdays*).

Following Deng et al. (2000), a measure of the net present value gain from refinancing a fixed rate mortgage (*refi*) is constructed as follows. At time *t*, the gain from refinancing is the percentage reduction in the discounted value of all future mortgage payments if the borrower refinances, PV_r, versus if the borrower continues to hold their current mortgage, PV_c:

$$refi_t = \left[\frac{PV_{ct} - PV_{rt}}{PV_{ct}}\right] \quad (10)$$

where

$$PV_{jt} = \sum_{m=0}^{RMT} \frac{P_{jt}}{(1+d_t)^m} \quad (11)$$

Where $j = c, r$, RMT is the remaining mortgage term in months, d_t, is the discount rate measured by the 30-year fixed conventional mortgage rate collected from the federal reserve (reported by Freddie Mac), and

$$P_{jt} = i_{jt} Q\left[\frac{(1+i_{jt})^{RMT}}{(1+i_{jt})^{RMT-1}}\right] \quad (12)$$

where i_{ct} is the market 30-year fixed mortgage interest rate at mortgage origination[Footnote7] at time *t* and i_{rt} is the market 30-year fixed mortgage interest rate at time *t*. We expect prepayment hazards to increase with *refi*, as defined in Eqs. 10 through 12.

We also include future interest and house price volatility measures, under the assumption that consumer expectations are rational and correctly forecast volatility. Interest rate volatility (*varmrate*) is the moving variance of future 24-month 30-year fixed-rate conventional mortgage rates and house price volatility (*varhpi*) is measured by the moving variance of future 24-month metropolitan area HPI. We expect that more volatility in interest rates will reduce refinance probabilities since borrowers may wait for interest rates to decline even further. Similarly, house price volatility increases the value of delaying default (Kau and Kim 1994 and Kau and Keenan 1995).To capture the effect of house price trends the number of months that house prices have been in decline (*ndecl*) is also included. This variable may capture how households and lender think about prices in the future and therefore affect the value of delay and the desire to move or refinance.

County unemployment rates are included to capture labor market conditions. Consistent with prior work, higher county unemployment rates indicate a higher probability that borrowers have lost their jobs or have a lower income stream, making it more difficult to make mortgage payments. Unemployment may also increase the use of "distressed" prepayments, but it also makes it harder to meet underwriting requirements to refinance.[Footnote8] To investigate the different roles of long run vs. short run local unemployment on mortgage terminations, we include different measures of cyclical and structural unemployment (observed, BN and HP cyclical and structural components). The average observed county unemployment rate is approximately 5.4 %.[Footnote9] Given the distressed nature of labor market it may be tempting to think that mortgage defaults may contribute to unemployment. Our empirical tests use individual loan data. The employment status of an individual should have an undetectable impact on unemployment rates; therefore, unemployment rates can be treated as exogenous to mortgage status.

Finally, we control for the impact of local foreclosure laws by including the average number of days from the start of foreclosure proceedings to the day when the property is referred for sale (*fdays*) in each state. Cutts and Merrill (2008) estimate this number using Freddie Mac data. It can serve as a proxy for the amount of "free rent" that a household can expect to gain during the foreclosure process and the cost of foreclosure that the lender/investor will bear in the event of a default. Due to the interaction of the lender and borrower the direction of the impact is an open empirical question.

Estimation Results

Our first set empirical specifications for competing risk, proportional hazard, with heterogeneity model include risk determinants standard in the literature.[Footnote10] Most of the estimates have signs consistent with expectations and are statistically significant. Borrower income relative to the metropolitan area median, credit score at origination, current loan-to-value ratio, and local unemployment rate are all strong indicators of default and prepayment probabilities. Higher income and credit scores (the prior ability to pay financial obligations in a timely fashion) are negatively associated with default and positively associated with prepayment. Higher c*ltv* is associated with higher default and lower prepayment probabilities. The variable *refi* is also a positive indicator for both default and prepayment. It is unclear why higher interest rates should drive up default probabilities in fixed rate loans; perhaps higher rates make competing household debt more costly, so that homeowners have a harder time paying the mortgage. As expected, we find that volatility in interest rates (*varmrate)* delays prepayment. However, we do not find that volatility in house prices (*varhpi*) delays default.

Berkovec et al. (1998), Calem and Wachter (1999), and Deng and Gabriel (2006) find that the debt-to-income ratio (*dti*) has little impact on mortgage termination. In contrast, we find a strong link between front-end ratio and prepayment. However, after controlling for income, the debt-to-income ratio is generally insignificant in the default equations.

All local unemployment rate measures (*unempr*) other than the HP cyclical component are positively associated with default and negatively associated with prepayment.[Footnote11] The HP cyclical component does not influence mortgage default significantly. The HP and BN cyclical components have a relatively small impact on mortgage terminations compared to the structural components. These results provide evidence that long run unemployment measures are a more important determinant of mortgage termination than cyclical unemployment.

Loan Termination Behavior and the Economic Environment

To better understand the link between mortgage terminations and the structural component and cyclical component of unemployment rates, we interact different measures of local unemployment with other explanatory variables in Tables 2 and 3.[Footnote12]

Table 2 Default sensitivity results

	Cyclical components						Structural components					
	Observed		HP		BN		HP		BN		HPRS	
	Coef	Std Err	Coef	Std Err	Coef	Std Err	Coef	Std Err	Coef	Std Err	Coef	Std Err
inc_ami	−0.355***	0.089	−0.266***	0.094	−0.265***	0.092	−0.355***	0.097	−0.358***	0.089	−0.144	0.112
dti	−0.096	0.090	−0.014	0.091	0.040	0.091	−0.163	0.101	−0.088	0.090	0.124	0.111
fico	−1.066***	0.088	−1.039***	0.087	−0.781***	0.083	−0.815***	0.102	−1.077***	0.086	−0.960***	0.098
cltv	0.505***	0.085	0.832***	0.087	0.570***	0.085	0.357***	0.094	0.503***	0.083	0.276**	0.112
unempr	0.300***	0.023	0.076***	0.026	0.036	0.022	0.324***	0.024	0.303***	0.023	0.168***	0.026
varmrate	−0.211**	0.084	0.402***	0.082	0.033	0.082	−0.164**	0.081	−0.207**	0.085	−0.418***	0.096
varhpi	0.086	0.059	−0.015	0.049	−0.101	0.080	0.062	0.083	0.078	0.058	0.391***	0.095
unempr_inc_ami	0.031*	0.017	0.014	0.020	0.016	0.020	0.030	0.019	0.032*	0.017	−0.009	0.023
unempr_dti	0.025	0.017	0.007	0.019	−0.003	0.020	0.039*	0.020	0.024	0.017	−0.018	0.023
unempr_fico	0.063***	0.019	0.063***	0.018	0.008	0.018	−0.001	0.021	0.066***	0.018	0.051**	0.020
unempr_cltv	0.006	0.016	−0.059***	0.018	−0.005	0.019	0.040**	0.018	0.006	0.016	0.061***	0.023
unempr_varmrate	0.049***	0.017	−0.107***	0.019	−0.019	0.018	0.023	0.015	0.049***	0.017	0.074***	0.020
unempr_varhpi	−0.007	0.009	0.021**	0.009	0.045***	0.017	−0.009	0.013	−0.006	0.009	−0.064***	0.020
loc1	−1.208***	0.117	−0.251**	0.127	−1.121***	0.209	−1.333***	0.118	−1.172***	0.118	−1.645***	0.211
loc2	−2.868***	0.458	−1.475***	0.289	0.031	0.113	−5.373***	0.963	−2.637***	0.298	−0.668***	0.130
q1	0		0		0		0		0		0	
q2	0.038	0.171	0.148	0.168	−0.366***	0.119	−0.276***	0.101	0.278**	0.141	−0.133	0.130
Loans	22,538		22,538		22,538		22,538		22,538		22,538	
Obs	968,561		968,561		968,561		968,561		968,561		968,561	
Loglike	−79,257		−79,401		−79,226		−79,071		−79,014		−79,439	

*indicates significance at 90 %, ** indicates significance at 95 %, and *** indicates significance at 99 %. *loc1* and *loc2* are shift parameters of the two heterogeneity groups. *q1* and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero. All unemployment variables are scaled to mean 4.5 and standard deviation 1 for identification. All other variables (other than the interaction terms) are scaled to mean 0 and standard deviation 1. *unempr* is the observed county unemployment rate, its HP cyclical component, its BN cyclical component, its HP structural component, its BN structural component, and its HP Ranking Score. These specifications are jointly estimated with Table 3.

Table 3 Prepayment sensitivity results

			Cyclical components				Structural components					
	Observed		**HP**		**BN**		**HP**		**BN**		**HPRS**	
	Coef	**Std Err**	**Coef**	**Std Err**	**Coef**	**Std Err**	**Coef**	**Std Err**	**Coef**	**Std Err**	**Coef**	**Std Err**
inc_ami	0.172***	0.056	0.140***	0.054	0.352***	0.054	0.270***	0.059	0.199***	0.057	0.288***	0.063
dti	0.165***	0.056	0.030	0.055	0.275***	0.055	0.285***	0.061	0.167***	0.057	0.063	0.062
fico	0.017	0.052	0.013	0.050	0.259***	0.047	0.141***	0.055	−0.001	0.053	0.268***	0.058
cltv	0.117**	0.050	−0.153***	0.048	−0.218***	0.050	0.164***	0.053	0.083*	0.050	−0.206***	0.060
refi	0.543***	0.061	0.368***	0.060	0.492***	0.062	0.651***	0.063	0.574***	0.062	0.665***	0.060
unempr	−0.128***	0.014	0.078***	0.013	−0.026**	0.012	−0.245***	0.014	−0.151***	0.014	−0.047***	0.013
varmrate	−0.427***	0.055	−0.296***	0.049	−0.207***	0.057	−0.388***	0.055	−0.309***	0.058	0.044	0.053
varhpi	0.302***	0.046	0.042	0.035	0.166***	0.059	0.444***	0.050	0.251***	0.046	0.018	0.058
unempr_inc_ami	0.039***	0.012	0.043***	0.011	0.002	0.012	0.015	0.013	0.035***	0.012	0.014	0.013
unempr_dti	0.013	0.012	0.040***	0.011	−0.012	0.012	−0.017	0.013	0.011	0.012	0.035***	0.013
unempr_fico	0.050***	0.011	0.046***	0.010	−0.004	0.010	0.022*	0.012	0.054***	0.011	−0.008	0.013
unempr_cltv	−0.072***	0.010	−0.023**	0.010	−0.014	0.011	−0.078***	0.011	−0.070***	0.011	−0.011	0.012
unempr_refi	−0.028**	0.014	−0.007	0.013	−0.005	0.014	−0.060***	0.014	−0.016	0.014	−0.063***	0.013
unempr_varmrate	0.051***	0.012	0.033***	0.011	0.023	0.012	0.045***	0.012	0.040***	0.013	−0.050***	0.012
unempr_varhpi	−0.059***	0.010	−0.008	0.007	−0.042*	0.013	−0.080***	0.010	−0.051***	0.010	−0.004	0.012
loc1	−0.352***	0.128	−1.324***	0.127	0.763***	0.068	0.433***	0.081	−0.437***	0.126	0.965***	0.080
loc2	1.354***	0.092	0.371***	0.092	−1.153***	0.116	1.880***	0.070	1.353***	0.080	−0.840***	0.112
q1	0		0		0		0		0		0	
q2	0.038	0.171	0.148	0.168	−0.366***	0.119	−0.276***	0.101	0.278*	0.141	−0.133	0.130
Loans	22,538		22,538		22,538		22,538		22,538		22,538	
Obs	968,561		968,561		968,561		968,561		968,561		968,561	
Loglike	−79,257		−79,401		−79,226		−79,071		−79,014		−79,439	

* indicates significance at 90 %, ** indicates significance at 95 %, and *** indicates significance at 99 %. *loc1* and *loc2* are shift parameters of the two heterogeneity groups. *q1* and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero. All unemployment variables are scaled to mean 4.5 and standard deviation 1 for identification. All other variables (other than the interaction terms) are scaled to mean 0 and standard deviation 1. *unempr* is the observed county unemployment rate, its HP cyclical component, its BN cyclical component, its HP structural component, its BN structural component, and its HP Ranking Score. These specifications are jointly estimated with Table 2

Again, most of the single variable estimates have signs consistent with expectations and are statistically significant. For default, the interaction results are most consistent for the credit score (*unempr_fico*) and the equity position (*unempr_cltv*) interactions. Default and prepayment are more sensitivity to credit scores at origination in areas with higher contemporaneous unemployment rates (measured by observed, cyclical, and structural components). We perform a number of simulations to demonstrate the impact of changes in the economic environment characterized by different unemployment measures. The hazards are simulated at the 37th month (around the first peaks of defaults) with all other characteristics evaluated at their means. We compare roughly one standard deviation above and below the mean of local unemployment and set the two comparison points at 4 % and 8 % for the observed and structural component and at −1 and 1 % unemployment rate for the cyclical component.

Figures 1 and 2 show the interaction between various measures of unemployment and the equity position of the borrower (current LTV). Higher c*ltv* is associated with a higher probability of default regardless of the economic condition. However, the magnitude of the impact might change. Figure 1 shows that changes in cyclical unemployment have little impact on the borrower behavior. On the other hand, higher levels of the structural component (HP Structural) increase the sensitivity of default to the equity position as illustrated in Figure 2. In summary, borrowers use the default option more aggressively when structural unemployment is high.

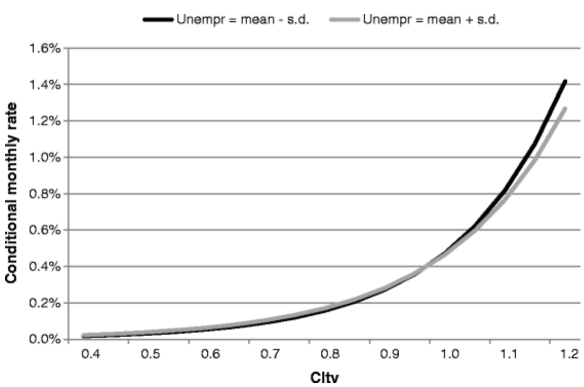

Fig. 1 Default, Cyclical HP Unemployment, and Current LTV. Note: Conditional monthly rate is estimated with sample mean characteristics (other than local unemployment rate and current loan-to-value ratio). Both series use "Cyclical HP" equation parameter estimates in Table 2. Loan age is set to 37th month. Unemployment rates are chosen for approximately one standard devaiton below and above the mean. More specifically, mean - s.d. = −1 % and mean + s.d. = 1 %

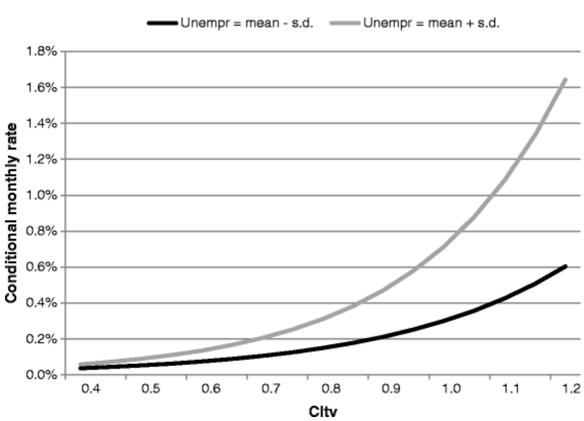

Fig. 2 Default, HP Structural Unemployment, and Current LTV. Note: Conditional monthly rate is estimated with sample mean characteristics (other than local unemployment rate and current loan-to-value ratio). Both series use "Structural HP" equation parameter estimates in Table 2. Loan age is set to 37th month. Unemployment rates are chosen for approximately one standard devaiton below and above the mean. More specifically, mean - s.d. = 4 % and mean + s.d. = 8 %

In terms of prepayment, the interactions are most consistent for the option proxy, *refi*, and borrower credit scores, *fico*. In addition, the structural components tend to dominate the cyclical components of unemployment. Locations with high rates of structural unemployment, whether measured by HP or BN, are also more sensitive to borrower credit history. In general, higher credit score borrowers are more likely to refinance or prepay the loan. When structural unemployment is high the relative difference between high and low credit score prepayment propensities is increased. However, a higher rate of structural unemployment depresses the responsiveness of borrowers to changes in interest rates. Therefore, when labor market conditions are structurally weak, credit history becomes even more important for maintaining access to credit markets and borrowers are less able to refinance existing debt when interest rates decline.

The Role of Expectations

Next, we examine the impact of borrower expectations on mortgage terminations. We test four variables: a 12-month forecast of future loan-to-value ratio (*cltv12*), a 12-month forecast of the future percentage gain on refinance (*refi12*), the number of months house prices have been declining (*ndecl*) and a measure of the number of days between a foreclosure referral and its referrer for sale in each state (*fdays*). The variable *fdays* is a proxy of the lenders costs of foreclosure and is largely determined by state regulations. It also proxies for how much "free rent" a delinquent borrower can gain while making no further mortgage payments.

The variable *cltv12* is defined as the ratio of the estimated outstanding loan balance to the expected house value 12 months from the date of each observation.[Footnote13] The outstanding loan balance is estimated according to the fixed rate amortization schedule for each loan and each period assuming the borrower stays current for the next 12 months. The expected house value is generated based on the metropolitan area house price index. A forecasting rule is generated on the stationary series and then forecasts of house value 12 months from the current period are generated for each loan and month.[Footnote14] Similarly, the variable *refi12* is generated based on a forecast of the market interest rate and remaining balance following the procedure described in Eqs. (10) to (12).

The estimates are presented in Tables 4 and 5. In the default model, we see *cltv12* is generally statistically insignificant. Therefore, borrowers do not seem more or less likely to default if the equity position is expected to increase or decrease. On the other hand, expectations of worsening equity positions deter refinancing and prepayment even more regardless of the specification. If prices have declined for a longer time in the past, refinances are deterred even more, after controlling for interest rates and future equity positions. Similar to the forward looking equity position, the backward looking price path (*ndecl*) does not have any consistently significant impact on default probabilities.

Table 4 Default results with expectations

	Observed		HP		BN		HPRS	
	Coef	Std Err	Coef	Std Err	Coef	Std Err	Coef	Std Err
inc_ami	−0.201***	0.024	−0.198***	0.024	−0.202***	0.024	−0.191***	0.023
dti	0.043*	0.023	0.047**	0.023	0.043*	0.023	0.049**	0.022
fico	−0.805***	0.027	−0.846***	0.024	−0.805***	0.027	−0.766***	0.026
cltv	0.496***	0.034	0.506***	0.041	0.497***	0.034	0.445***	0.035
cltv12	0.013	0.035	−0.007	0.041	0.014	0.035	0.073**	0.035
observed	0.242***	0.021						
cyclical			−0.009	0.021	−0.011	0.018		
structural			0.358***	0.023	0.244***	0.021	0.160***	0.021
ndecl	−0.010	0.022	−0.033	0.022	−0.011	0.022	0.045**	0.020

varmrate	0.020	0.021	−0.049**	0.023	0.020	0.021	−0.070***	0.020
varhpi	0.054***	0.018	0.004	0.020	0.055***	0.018	0.071***	0.017
fdays	0.011	0.022	−0.027	0.023	0.012	0.022	0.003	0.021
loc1	−1.810***	0.403	−2.714***	0.655	−1.820***	0.406	−1.181***	0.245
loc2	0.253***	0.046	0.258***	0.068	0.252***	0.046	0.240***	0.047
q1	0		0		0		0	
q2	−0.121	0.145	0.040	0.188	−0.118	0.145	−0.257*	0.152
Loans	21,315		21,315		21,315		21,315	
Obs	936,828		936,828		936,828		936,828	
Loglike	−74,683		−74,487		−74,681		−74,751	

* indicates significance at 90 %, ** indicates significance at 95 %, and *** indicates significance at 99 %. *loc1* and *loc2* are shift parameters of the two heterogeneity groups. *q1* and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero. All unemployment variables are scaled to mean 4.5 and standard deviation 1 for identification. All other variables (other than the interaction terms) are scaled to mean 0 and standard deviation 1. These specifications are jointly estimated with Table 5

Table 5 Prepayment results with expectations

	Level		**HP**		**BN**		**HPRS**	
	Coef	**Std Err**	**Coef**	**Std Err**	**Coef**	**Std Err**	**Coef**	**Std Err**
inc_ami	0.348***	0.014	0.320***	0.013	0.348***	0.014	0.349***	0.014
dti	0.184***	0.014	0.168***	0.013	0.184***	0.014	0.184***	0.014
fico	0.287***	0.013	0.260***	0.012	0.287***	0.013	0.272***	0.013
cltv	−0.161***	0.035	−0.152***	0.033	−0.162***	0.035	−0.133***	0.035
cltv12	−0.078**	0.034	−0.068**	0.033	−0.077**	0.034	−0.129***	0.034
refi	0.479***	0.051	0.480***	0.051	0.479***	0.051	0.509***	0.051
refi12	0.045	0.051	−0.063	0.051	0.045	0.051	−0.021	0.051
observed	−0.151***	0.013						
cyclical			0.134***	0.014	−0.002	0.011		
structural			−0.277***	0.013	−0.151***	0.013	−0.115***	0.013
ndecl	−0.089***	0.015	−0.076***	0.015	−0.088***	0.015	−0.129***	0.015
varmrate	−0.105***	0.013	−0.056***	0.013	−0.104***	0.013	−0.067***	0.013
varhpi	0.014	0.012	0.065***	0.011	0.012	0.012	0.015	0.012
fdays	0.138***	0.014	0.151***	0.013	0.137***	0.014	0.144***	0.014
loc1	0.628***	0.051	0.518***	0.053	0.629***	0.051	0.587***	0.051
loc2	−1.064***	0.097	−0.754***	0.096	−1.061***	0.097	−1.150***	0.109
q1	0		0		0		0	
q2	−0.121	0.145	0.040	0.188	−0.118	0.145	−0.257*	0.152
Loans	21,315		21,315		21,315		21,315	
Obs	936,828		936,828		936,828		936,828	
Loglike	−74,683		−74,487		−74,681		−74,751	

* indicates significance at 90 %, ** indicates significance at 95 %, and *** indicates significance at 99 %. *loc1* and *loc2* are shift parameters of the two heterogeneity groups. *q1* and *q2* are logistic transformation parameters for the heterogeneity mass points. *q1* is normalized to zero. All unemployment variables are scaled to mean 4.5 and standard deviation 1 for identification. All other variables (other than the interaction terms) are scaled to mean 0 and standard deviation 1. These specifications are jointly estimated with Table 4

Expectations of future interest rates had no additional impact on refinancing activity or prepayment. This result may indicate that borrowers are willing to exercise the prepayment option whenever it is in the money and the costs of refinancing may have become so low that there is little incentive for borrowers to wait for lower interest rates in the future.

Finally, we find that expectations about lender costs and borrower benefits, captured with foreclosure days (*fdays*), do not influence the default decisions. These higher costs, however, do seem to make prepayment a more attractive option. Long foreclosure proceedings may give defaulting households enough time to find a buyer for the home; or, by increasing the cost of default, incentivize lenders/investors to accept short sales (a sale of the property to extinguish the debt even if the proceeds do not cover the outstanding debt and fees).

In summary, most of the forward looking variables tend to have an impact of prepayment but not on defaults.

Serious Delinquency vs. Short-Term Delinquency

Finally, we conduct a preliminary investigation of short-term or 30-day delinquency patterns. We estimate a specification similar to the one presented in Table 4. The new default results are presented in Table 6. We focus our discussion on two variables: *unempr* and *fdays*. Higher local unemployment increases the propensities of 30-day delinquency. This is especially true for structural unemployment. We also find HP cyclical component also increases the 30-day delinquency propensity. Higher expected lender costs/borrower benefits (*fdays*) are associated with a higher incidence of short-term delinquency but are not associated with serious delinquency (default). This provides suggestive evidence that borrowers are aware of how long a foreclosure takes. In states where the foreclosure timeline is very long, borrowers should be less worried about losing the home and are more willing to be temporarily delinquent on their mortgage. In contrast, the foreclosure timeline has no impact on serious delinquency (default).

Table 6 30-days delinquency results with expectations

	Observed		**HP**		**BN**		**HPRS**	
	Coef	**Std Err**	**Coef**	**Std Err**	**Coef**	**Std Err**	**Coef**	**Std Err**
inc_ami	−0.112***	0.023	−0.123***	0.026	−0.113***	0.023	−0.119***	0.022
dti	0.102***	0.022	0.121***	0.028	0.101***	0.022	0.084***	0.021
fico	−0.839***	0.022	−0.957***	0.024	−0.839***	0.022	−0.814***	0.021
cltv	0.246***	0.049	0.174***	0.054	0.246***	0.049	0.168***	0.054
cltv12	−0.136***	0.044	−0.083*	0.046	−0.136***	0.044	0.039	0.048
observed	0.493***	0.017						
cyclical			0.042**	0.019	−0.019	0.014		
structural			0.728***	0.025	0.499***	0.018	0.132***	0.020
ndecl	0.216***	0.014	0.177***	0.014	0.212***	0.015	0.320***	0.017
varmrate	0.015	0.019	−0.098***	0.021	0.016	0.019	−0.210***	0.018
varhpi	0.013	0.015	−0.080***	0.019	0.015	0.015	0.074***	0.015
fdays	0.059***	0.021	0.022	0.023	0.061***	0.021	0.075***	0.020
loc1	−5.351***	0.404	−1.438***	0.056	−5.296***	0.396	−7.132***	1.048
loc2	−1.766***	0.042	−5.110***	0.167	−1.765***	0.043	−1.790***	0.035
q1	0		0		0		0	
q2	1.106***	0.112	0.022	0.114	1.098***	0.113	1.607***	0.110
Loans	21,310		21,310		21,310		21,310	
Obs	909,035		909,035		909,035		909,035	
Loglike	−76,867		−76,544		−76,862		−77,269	

* indicates significance at 90 %, ** indicates significance at 95 %, and *** indicates significance at 99 %. *loc1* and *loc2* are shift parameters of the two heterogeneity groups. *q1* and *q2* are logistic transformation

parameters for the heterogeneity mass points. *q1* is normalized to zero. All unemployment variables are scaled to mean 4.5 and standard deviation 1 for identification. All other variables (other than the interaction terms) are scaled to mean 0 and standard deviation 1. These specifications are jointly estimated with prepayment (results not shown)

Conclusions

In the wake of the recent economic crisis, many government programs have been designed specifically to help homeowners avoid foreclosures. They include the Emergency Homeowners' Loan Program run by the Department of Housing and Urban Development and the Hardest Hit Fund run by Department of Treasury and authorized under the Emergency Economic Stabilization Act of 2008. The local unemployment situation inevitably becomes an important criterion when targeting resources to deal with the crisis. While the observed local unemployment rate is an important determinant of mortgage termination, we find that the long run or structural unemployment rate is a more important determinant of mortgage terminations. In contrast, short run or cyclical unemployment rates play a very small role. Therefore, policy interventions could be more effective if they target resources on locations with high structural unemployment. For example, as Figure 2 has shown, states like California and Michigan have suffered high levels of structural unemployment rate during the recent recession. Florida has suffered an increase in structural unemployment in many of its counties. These states were among the hardest hit in terms of mortgage default and foreclosures during the recent housing crisis. On the other hand, States like Texas have seen modest structural local unemployment compared to the rest of the nation during the recent crisis, and they have seen relatively modest level of mortgage delinquency.

The way unemployment is measured matters. Default and prepayment probabilities are more responsive to changes in the long run (structural) local unemployment rate when measured with the HP filter than when measured by changes in the observed local unemployment rate. The probability of mortgage default is much higher for households in areas where structural unemployment is high. In contrast, when the BN procedure is used there is little differential impact. Future work needs to explore this issue further.

We also find that the impacts of risk factors can vary significantly depending on the economic environment. For example, when structural unemployment rates are high, loans are more sensitive to the amount of equity in the home. In particular, homeowners are more likely to default when structural employment conditions are weak. This effect is not found for cyclical employment conditions. In terms of the incentives to refinance, when structural employment conditions are weak households are less responsive to declining interest rates. In addition, credit scores matter even more for both default and prepayment when structural unemployment is high. In short, while access to credit markets is greatly hampered by high rates of structural unemployment, the impact is softened for those with better credit histories.

We find that expectations affect some mortgage outcomes. Expectations of higher lender foreclosure costs and longer free rent have no effect on serious delinquencies, but are associated with increased prepayments. One explanation is that the higher default costs may make the alternative option (prepayment) relatively less costly leading to more workouts and short sales. In contrast to the serious delinquency results, loans in states with longer foreclosure procedure are more likely to have short-term (30 days) delinquency than loans in more lender-friendly states. The reasons are not entirely clear in the literature. One explanation could be that these results may reflect the recognition by borrowers that there is plenty of time to cure a loan with a modest amount of delinquency in a state with a longer foreclosure time line. These results can shed some light on how borrowers may react to the lengthening of the foreclosure timeline for other reasons. For example, some lenders have imposed foreclosure moratoria due to legal concerns over the documentation used during the foreclosure process.

In sum, this study provides empirical evidence of the link between long run or structural unemployment and mortgage termination through default and prepayment. The results indicate that if attempts to intervene in the labor market are to have meaningful impacts on mortgage markets, the intervention may be more effective if targeted to areas of high structural local unemployment.

Notes

1. It has been argued that the US unemployment rate is stationary (see Mocan 1999 for a review), especially given that it is bounded by definition. This study simply relies on the particular unit root test as the basis for examining different de-trending techniques.
2. τ_t and c_t represent structural and cyclical component in both BN decomposition and HP filter.
3. Applying a more elaborated routine to determine the ARMA process for each unemployment series may not be practical (for example, Clements et al. 2007 discuss forecast evaluations).
4. The choice of smoothing parameter has little impact on empirical results. For example, when we set the smoothing parameter to 110,000, a roughly 10 percent change from 129,600 (while still within reasonable set up according to Ravn and Uhlig 2002) the change in structural component is too small.
5. See Quercia et al. (2009) for a brief overview of the data.
6. Following Pennington-Cross and Ho (2010), we standardize each variable to a mean of 0 and a standard deviation of 1 to aid convergence of the likelihood function. Because we are interested in the interaction of unemployment with other risk determinants, we normalize unemployment variables to a mean of 4.5 (and standard deviation 1).
7. This is done to control for possible endogenous mortgage interest rate on current mortgage.
8. "Distressed" prepayments are loans that are paid off early or refinanced because the borrower is under financial stress. For example, these prepayments could include a cash-out feature that is used for consumption or to pay off other outstanding debt obligations.
9. Decomposition usually implies that the average of the structural components of unemployment rates are supposed to be very close to the average of the level while the average of the cyclical components tends to zero.
10. Baseline specification results are included in the working paper. Results not included in the final paper are available upon request.
11. Controlling both cyclical and structural components in the same models requires interpretation of the changing one holding the other constant. For simulation purposes, we include these components in separate regressions and allow each component moving freely. When estimated together, cyclical components are largely insignificant other than the prepayment results for HP cyclical component. For example, when estimated jointly with respective structural components, the cyclical component point estimates of default for HP is −0.01 (insignificant), of default for BN is −0.01 (insignificant), and of prepayment for BN is −0.005 (insignificant). Those results are similar with results including expectations presented later.
12. Although individual mortgage defaults are very unlikely to affect unemployment rates, it is true that the typical macro-economic variables used in a default and prepayment specification are jointly determined in the overall economic and financial markets. To partially control for this we include specifications that include the direct impact of the variable and it's interaction with the unemployment rate (observed, cyclical and structural).
13. Additional specifications used the expected change in *cltv* and the results are very similar (robust).
14. HPI series are either I(0) or I(1) for all cities and each forecasting rule is based on an ARMA process selected by information criteria.

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